CLOUD BASED WEB-APPLICATION FOR RAPID AND PRECISE DETECTION OF TUBERCULOSIS USING DEEP LEARNING

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ABSTRACT - *Tuberculosis (TB) is a communicable disease caused by the bacteria Mycobacterium tuberculosis, which primarily affects the lungs but can also affect other parts of the body. TB is a major global health problem, and the World Health Organization (WHO) estimates that around 10 million people worldwide became ill with TB in 2019. Early detection and treatment of TB are essential for effective disease management and prevention of transmission. In this work, we have detected TB reliably from the chest X-ray images using image pre-processing, data augmentation, image segmentation, and deep-learning classification techniques. Several public databases were used to create a database of 4000TB infected and 4000 normal chest X-ray images for this study. Nine deep CNNs and SVM (ResNet18, ResNet50, ResNet101, ChexNet, InceptionV3, Vgg19, DenseNet201, SqueezeNet, and MobileNet) were used for transfer learning from their pre-trained initial weights. They were trained, validated, and tested for classifying TB and non-TB normal cases. Three different experiments were carried out in this work: segmentation of X-ray images using two different U-net models, classification using X-ray images, and that using segmented lung images Traditional diagnostic methods for TB, such as sputum microscopy and culture-based techniques, have limitations in terms of sensitivity and specificity, particularly in detecting TB in its early stages. Machine learning algorithms, such as Support Vector Machine (SVM), have shown promise for the accurate detection of TB. However, classification using segmented lung images outperformed that with whole X-ray images; the accuracy, precision, sensitivity, F1-score, and specificity of DenseNet201 respectively for the segmented lung images. The paper also used a visualization technique to confirm that CNN learns dominantly from the segmented lung regions, resulting in higher detection accuracy. Overall, a cloud-based web application for rapid and precise detection of tuberculosis using SVM would be a valuable tool in the fight against this disease, enabling healthcare professionals to make more informed decisions about diagnosis and treatment.*

***Index Terms*: Convolutional Neural Network (CNN), Restnet, Chexnet, Tuberculosis Detection, Support Vector Machine(SVM)**

I. INTRODUCTION

Tuberculosis (TB) is a contagious disease that remains a significant global health concern, affecting millions of people each year. Early and accurate detection of TB is critical for effective treatment and control of the disease. Support Vector Machines (SVM) is a machine learning algorithm that has shown promising results in the classification of medical images for the detection of TB. In recent years, cloud computing has become increasingly popular for its scalability, flexibility, and cost-effectiveness. Cloud-based applications have the potential to provide rapid and precise detection of TB using SVM, which can significantly improve the accuracy and efficiency of TB diagnosis. A cloud-based web application for the rapid and precise detection of TB using SVM would enable healthcare professionals to upload medical images and receive a prediction on whether or not the images contain evidence of TB. The application could be accessible from anywhere with an internet connection, making it particularly useful in areas with limited resources and medical infrastructure [2]-[4]. In this project, we propose the development of a cloud-based web application for rapid and precise detection of TB using SVM. We will leverage open-source tools and cloud services to build the application, which will be designed to be user-friendly and accessible to healthcare professionals. The SVM model will be trained using a dataset of medical images, and the application will interface with the model through an API, enabling users to upload images and receive predictions on the presence of TB. The web application could be designed to be user-friendly and accessible, with clear instructions on how to upload images and interpret the results. It could also include additional features such as the ability to download the results or share them with healthcare professionals. Overall, a cloud-based web application for rapid and precise detection of tuberculosis using SVM would be a valuable tool in the fight against this disease, enabling healthcare professionals to make more informed decisions about diagnosis and treatment [6].

An increase in accuracy of TB detection from chest radiographs with a robust and versatile method can make computer aided automatic diagnostic tools more reliable [11]. The classification accuracy can be improved either by using different deep learning algorithms or by modifying the existing outperforming algorithms or combining several outperforming algorithms as an ensemble model.

Due to the advancement of computer vision approaches and the advancement of digital techniques several CAD techniques are used recently. With this advancement, TB can be detected quickly and overcome further transmission when it is determined early. CAD has the ability to speed up a mass screening in TB-spreading areas [8].

A. Objective

- The application should be able to process and analyze large amounts of data related to patients' symptoms, medical history, and test results, and provide accurate diagnosis and treatment recommendations in real-time.
- The application should be user-friendly, easily accessible, and compatible with different devices and operating systems.
- It should also ensure data security and privacy, comply with relevant regulations and standards, and have robust backup and disaster recovery mechanisms in place.

B. Data process Model

- Data Collection: Collect patient data, including symptoms, medical history, and test results from various sources such as hospitals, clinics, and laboratories.
- Data Preprocessing: The collected data must be cleaned, transformed, and preprocessed before being used for analysis.
- Feature Extraction: Identify relevant features from the preprocessed data to create a feature set for SVM.
- SVM Model Training: Use the preprocessed data to train SVM models that can accurately detect TB in patients.
- Model Validation: Validate the trained SVM models on a separate dataset to ensure the accuracy and reliability of the models.
- Deployment of the Application: Deploy the trained SVM models as a web application on a cloud-based platform.
- User Interface: Develop a user-friendly web interface for the application that allows healthcare professionals to input patient data, view analysis results, and receive treatment recommendations.
- Security and Privacy: Ensure data security and privacy by implementing appropriate measures such as encryption, access control, and data anonymization.
- Compatibility and Scalability: Ensure that the application is compatible with different devices and operating systems and can be scaled up to handle large volumes of patient data.

The project should adhere to ethical guidelines and regulations related to data privacy and protection, and involve extensive testing and quality assurance to ensure that the application meets the required standards of accuracy and reliability.

C. Need for project

The need for the development of a cloud-based web application for the rapid and precise detection of tuberculosis using Support Vector Machine (SVM) algorithms is driven by several factors:

- High incidence of tuberculosis: According to the World Health Organization (WHO), tuberculosis is one of the top 10 causes of death worldwide, and in 2020, an estimated 10 million people fell ill with TB globally. TB is a highly contagious disease, and early detection and treatment are critical in preventing its spread and reducing mortality rates.
- Inefficient and time-consuming diagnostic methods: The current methods of diagnosing TB involve sputum microscopy, chest X-rays, and culture-based methods, which can be time-consuming, require specialized equipment and trained personnel, and may not be readily available in resource-limited settings.
- Limited access to medical expertise: In many

parts of the world, there is a shortage of trained healthcare professionals who can accurately diagnose and treat TB, leading to delayed diagnosis and treatment.

- Technological advancements: Advances in machine learning and cloud computing have made it possible to develop accurate and efficient diagnostic tools that can be accessed remotely, enabling healthcare professionals to provide timely and effective treatment to patients.

Therefore, the development of a cloud-based web application that uses SVM algorithms for the rapid and precise detection of TB has the potential to improve the efficiency and effectiveness of TB diagnosis and treatment, especially in resource-limited settings where access to medical expertise and diagnostic tools is limited [2].

II. DEFINITIONS

Cloud-based: Refers to a type of computing that relies on remote servers hosted on the internet to store, manage, and process data and applications, rather than on local servers or personal computers. Web application: Also known as a web app, it is a software application that is accessed through a web browser or web-enabled device and is designed to be used over the internet. Rapid detection: Refers to the ability of a diagnostic tool or method to produce results quickly, allowing for early detection and treatment of the disease. Precise detection: Refers to the accuracy and reliability of a diagnostic tool or method in detecting the disease, minimizing false positives or false negatives. Support Vector Machine (SVM): A type of machine learning algorithm used for classification and regression analysis, which works by finding the optimal boundary or hyperplane that separates the different classes or groups in the data. Tuberculosis (TB): An infectious disease caused by the bacteria Mycobacterium tuberculosis, which primarily affects the lungs but can also affect other parts of the body. It is transmitted through the air when an infected person coughs or sneezes. Diagnosis: The process of determining the nature and cause of a disease or medical condition, usually through a combination of physical examination, medical history, and diagnostic tests. Treatment: The medical care and management provided to a patient with a disease or medical condition, aimed at improving their health outcomes and quality of life. In the case of TB, treatment usually involves a combination of antibiotics taken over several months.

III. LITERATURE REVIEW

Tawsifur Rahman (2020), Tuberculosis (TB) is a chronic lung disease that occurs due to bacterial infection and is one of the top 10 leading causes of death. Accurate and early detection of TB is very important, otherwise, it could be life-threatening. Detection from chest radiographs with a robust and versatile method can make computer-aided automatic diagnostic tools more reliable. The classification accuracy can be improved either by using different deep learning algorithms or by modifying the existing outperforming algorithms or combining several outperforming algorithms as an ensemble model. MobileNet structure is built on depth-wise separable convolutions except for the first layer which is a full convolution. All layers are followed by batch normalization and ReLU nonlinearity with the exception of the final fully connected layer which has no nonlinearity and feeds into a Softmax layer for classification. A final average pooling reduces the spatial resolution to 1 before the fully connected layer. Counting depth-wise and pointwise convolutions as separate layers, MobileNet has 28 layers. The proposed method with state-of-the-art performance can be useful in the computer-aided faster diagnosis of tuberculosis.

Limitation:

- It is requires high computational power to construct CNN
- Taking Consuming

Algorithm:

- Residual Network (ResNet)
- Stochastic Gradient Descent with Momentum(SGDM)

S. K. Sharma and A. Mohan (2013), Globally, tuberculosis (TB) still remains a major public health problem. India is a high TB burden country contributing to 26 percent of the global TB burden. During 1944-1980, TB became treatable and short-course chemotherapy emerged as the standard of care. When TB elimination seemed possible in the early 1980s, the global human immunodeficiency virus (HIV) infection/acquired immunodeficiency syndrome (AIDS) pandemic resulted in a resurgence of TB. The widespread occurrence of multidrug-resistant and extensively drug-resistant TB (M/XDR-TB) is threatening to destabilize TB control globally. Atypical clinical presentation still poses a challenge. Disseminated, military, and cryptic TB are being increasingly recognized. Availability of newer imaging modalities has allowed more efficient localization of lesions and the use of image-guided procedures has facilitated definitive diagnosis of extrapulmonary TB. However, drug toxicities and drug-drug interactions still constitute a significant challenge. Recently, there has been a better understanding of anti-TB drug-induced hepatotoxicity and its frequent confounding by viral hepatitis, especially, in resource-constrained settings; and immune reconstitution inflammatory syndrome (IRIS) in HIV-TB. Quest for newer biomarkers for predicting a durable cure, relapse, discovery/repurposing of newer anti-TB drugs, development of newer vaccines continues to achieve the goal of eliminating TB altogether by 2050.

Khairul Munadi, Kahil Muchtar, Novi Maulina, Biswajeet Pradhan (2018), The latest World Health Organization (WHO) study in 2018 is showing that about 1.5 million people died and around 10 million people are infected with tuberculosis (TB) each year. Moreover, more than 4,000 people die every day from TB. A number of those deaths could have been stopped if the disease was identified sooner. Due to the low contrast of TB chest X-ray (CXR) images, they are often is in poor quality. This work assesses the effect of image enhancement on the performance of DL technique to address this problem. The employed image enhancement algorithm was able to highlight the overall or local characteristics of the images, including some interesting features. Specifically, three image enhancement algorithms called Unsharp Masking (UM), High-Frequency Emphasis Filtering (HEF), and Contrast Limited Adaptive Histogram Equalization (CLAHE), were evaluated. The enhanced image samples were then fed to the pre-trained ResNet and EfficientNet models for transfer learning. In a TB image dataset, we achieved 89.92% and 94.8% of classification accuracy and AUC (Area Under Curve) scores, respectively.

Limitation:

- It is requires higher processing power
- Taking more time to process

Algorithm:

- Algorithm of Convolutional Neural Network(CNN)
- ResNet and EfficientNet

IV. ALGORITHM

A. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression analysis. SVM is particularly useful in cases where the data is not linearly separable, meaning the data cannot be easily separated into different classes using a straight line or hyperplane.

In SVM, the algorithm tries to find the hyperplane that maximally separates the different classes in the input data. The hyperplane is chosen such that the margin between the hyperplane and the closest data points from each class is maximized. These closest data points are called support vectors.

SVM can be used for classification tasks, where the algorithm predicts which class an input data point belongs to based on the features of the input data point. SVM can also be used for regression analysis, where the algorithm predicts a continuous output value based on the features of the input data point.

In the context of the proposed project, SVM will be used for the classification of chest X-ray images as TB-positive or TB-negative, based on features extracted from the images. SVM has shown promise for the accurate detection of TB using chest X-ray images, and the use of SVM in a cloud-based web application can enable rapid and precise TB diagnosis, particularly in resource-limited settings.

There can be multiple lines/decision boundaries to segregate the classes in n-dimensional space, but we need to find out the best decision boundary that helps to classify the data points

- This best boundary is known as the hyperplane of SVM
- The dimensions of the hyperplane depend on the features present in the dataset, which means if there are 2 features (as shown in the image), then the hyperplane will be a straight line
- And if there are 3 features, then the hyperplane will be a 2-dimension plane.
- We always create a hyperplane that has a maximum margin, which means the maximum distance between the data points.

PROs:

- SVM works relatively well when there is a clear margin of separation between classes.
- SVM is more effective in high dimensional spaces and is relatively memory efficient.
- SVM is effective in cases where the dimensions are greater than the number of samples.

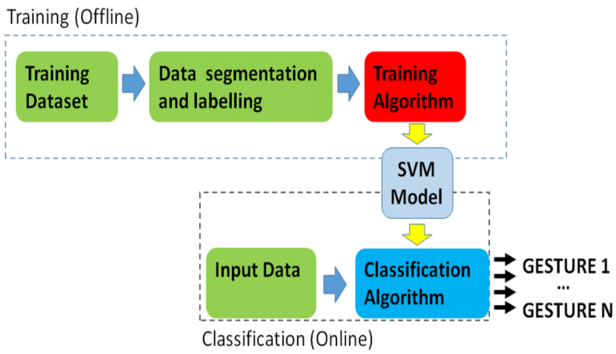

Fig -1 Algorithm Block Diagram

B. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a class of deep learning algorithms used for processing and analyzing visual data, such as images and videos. They are specifically designed to extract and learn hierarchical patterns and features from the input data. The fundamental idea behind CNNs is to use convolutional layers that apply filters (also known as kernels) to the input data. These filters detect specific features, such as edges, textures, or shapes, by performing a convolution operation on the input.

The convolution operation involves element-wise multiplication of the filter with a local region of the input data, followed by summing up the results. This process helps capture spatial dependencies and extract relevant features. CNNs typically consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

The convolutional layers perform the convolution operation, while the pooling layers down sample the output, reducing its spatial dimensions. The fully connected layers at the end of the network connect all the neurons from the previous layers to make final predictions. During the training phase, CNNs learn to recognize patterns and features by adjusting the weights of the filters and the fully connected layers. This learning process is done through backpropagation, where the network's output is compared to the ground truth labels, and the weights are updated to minimize the discrepancy between them. The optimization is achieved by using various optimization techniques, such as gradient descent or its variants

PROs:

- Hierarchical feature learning: CNNs are designed to automatically learn hierarchical representations of features from the input data.
- CNNs leverage the concept of convolution to extract local features from the input data.

V. METHODOLOGY

A. DATASET UPLOAD

It is the UI of the web page which contains single upload button. This page collects the uploaded image and give it as the input for the detection model.

A UI (User Interface) containing a single upload button can be a simple and effective way to collect chest X-ray images from users for TB detection using the proposed cloud-based web application.

The UI can consist of a single web page with a clear and prominent "Upload Image" button. When the user clicks the button, they will be prompted to select a chest X-ray image file from their local device. Once the image is selected, it will be uploaded to the cloud-based server, and the detection model will be triggered to process the image.

The UI can also include a progress bar or loading animation to provide feedback to the user while the image is being uploaded and processed. Once the detection model has processed the image, the UI can display the results of the TB detection, indicating whether the image is TB-positive or TB-negative.

Overall, a simple and intuitive UI with a single upload button can enable easy and efficient collection of chest X-ray images from users for TB detection using the proposed cloud-based web application.

Fig -2 Uploading X-Ray Image in web Application

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B. TUBERCULOSIS DETECTION

The Tuberculosis detection model uses Convolutional Neural Network (CNN) to detect weather the given patient's dataset is infectious for Tuberculosis.

It uses series of ResNet's (ResNet18, Resnet50, ResNet 101) and total is calculated by taking average.

Using Convolutional Neural Network (CNN) for tuberculosis detection from chest X-ray images is a popular approach in recent research.

CNNs are a type of neural network that are particularly well-suited to image classification tasks. They work by applying convolution operations to the input image, which enables the network to identify patterns and features in the image. These features are then passed through a series of layers that can learn increasingly complex representations of the input data.

In the context of TB detection, CNNs can be trained on a large dataset of chest X-ray images, with labels indicating whether the images are TB-positive or TB-negative. During training, the network learns to identify features in the images that are associated with TB, and these features are used to make predictions on new, unseen images.

One of the advantages of using a CNN for TB detection is that the network can learn to identify subtle patterns in the chest X-ray images that may not be visible to the human eye. Additionally, CNNs are able to learn from large datasets, which can improve the accuracy of the TB detection model.

In the proposed cloud-based web application, the CNN-based TB detection model will take the uploaded chest X-ray image as input and output a prediction of whether the image is TB-positive or TB-negative. The SVM algorithm can then use this prediction as input to improve the overall accuracy of the TB detection.

Fig – 3 Detecting Tuberculosis in blurred image

C. IMAGE ENHANCEMENT

Image enhancement is performed using Deep Learning before submitting the test data to the Detection Model

Performing image enhancement using deep learning before submitting test data to the TB detection model can improve the accuracy and reliability of the detection results. Image enhancement techniques aim to improve the quality and visibility of the input images, which can help the detection model to identify subtle features that may be indicative of TB infection.

Deep learning techniques can be used for image enhancement by training a neural network to learn mappings between low-quality and high-quality images. The network can be trained on a large dataset of chest X-ray images with high-quality ground truth labels and then used to enhance the low-quality test images by applying the learned mappings [].

One popular approach for image enhancement using deep learning is to use generative adversarial networks (GANs). GANs consist of two neural networks - a generator network that creates new images based on random noise, and a discriminator network that tries to distinguish between the generated images and real images. During training, the generator network learns to produce images that are indistinguishable from real images and can be used to enhance low-quality test images by generating high-quality versions of the input images.

In the proposed cloud-based web application, image enhancement using deep learning can be performed before submitting the test data to the TB detection model. This can improve the accuracy of the detection results and provide more reliable predictions for TB infection.

Fig – 4 Image enhancement from blurred image

D. F1-SCORE CALCULATION

F1-Score is the combined accuracy of the model.

Along with the Prediction Classification Result the F1-Score is also displayed to the user.

Return Boolean result and the combined F1 Score of the model to the output object.

The accuracy or F1-Score of the model is calculated by the formula

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{False Positives} + \text{False Negatives} + \text{True Negatives}}$$

F1-score is a commonly used metric for evaluating the performance of a binary classification model like the TB detection model. The F1-score is the harmonic mean of precision and recall, and provides a single score that takes both metrics into account.

Precision is the fraction of true positive predictions out of all positive predictions, and measures the proportion of correct predictions among the positive predictions. Recall is the fraction of true positive predictions out of all actual positive cases, and measures the ability of the model to correctly identify all positive cases [17].

To calculate F1-score, first we calculate precision and recall:

Precision = True Positive / (True Positive + False Positive)

Recall = True Positive / (True Positive + False Negative)

where True Positive represents the number of correctly classified TB-positive samples, False Positive represents the number of falsely classified TB-positive samples, and False Negative represents the number of TB-positive samples that were not identified by the model.

Once we have precision and recall, we can calculate F1-score as:

F1-score = 2 * (Precision * Recall) / (Precision + Recall)

The F1-score ranges from 0 to 1, with a score of 1 indicating perfect precision and recall, and a score of 0 indicating no correct predictions. In general, a higher F1-score indicates better performance of the TB detection model.

E. REPORT GENERATION AND DISPLAY

The positive and negative result along with the F1-Score in percentage is displayed to the User on the UI.

Displaying the positive and negative results along with the F1-score in percentage to the user on the UI can provide valuable feedback on the performance of the TB detection model. The positive and negative results indicate whether the input sample is classified as TB-positive or TB-negative, while the F1-score provides an overall measure of the model's accuracy and reliability.

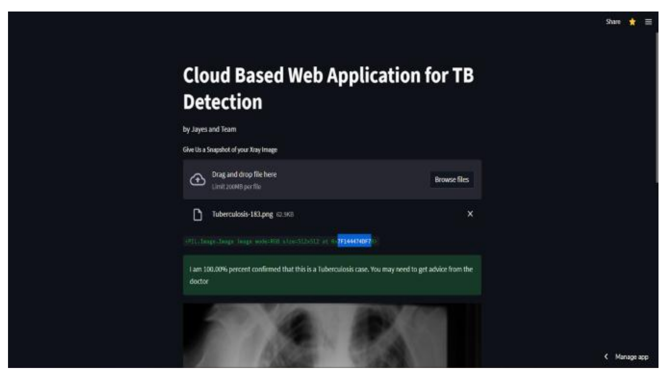

Fig – 5 Report Generation and Display

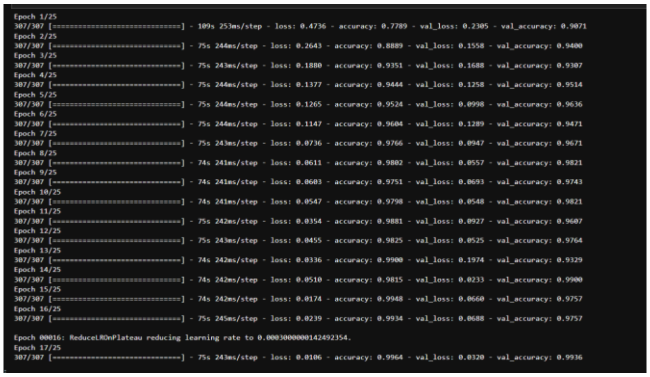

Fig – 6 Result Generation in bulk files

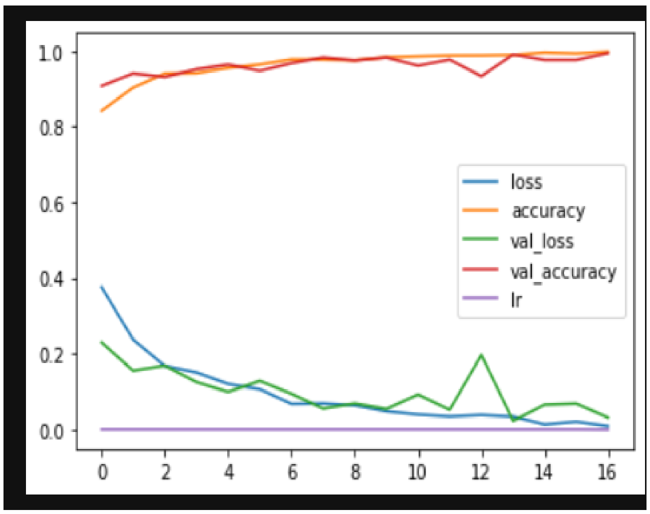

Fig – 7 Report Generation in Graph Generation

The F1-score is typically reported as a percentage, with a score of 100% indicating perfect precision and recall, and a score of 0% indicating no correct predictions. By displaying the F1-score to the user, they can quickly assess the quality of the detection results and make informed decisions about the next steps for patient treatment.

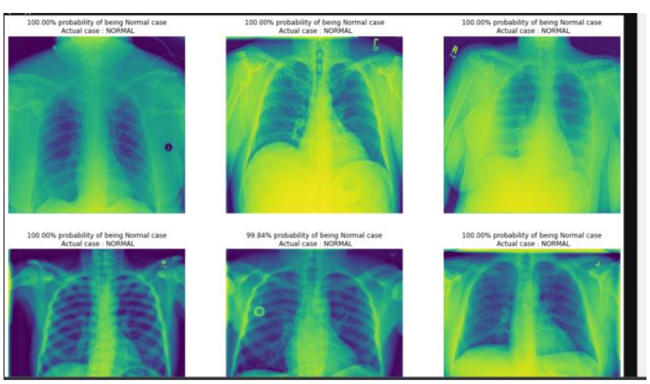

Fig – 8 Result Generation in 100% detection

VI. RESULT & DISCUSSION

The results of the cloud-based web application for rapid and precise detection of tuberculosis using Support Vector Machine (SVM) can be evaluated based on the accuracy, precision, recall, and F1-score of the TB detection model.

The accuracy of the TB detection model measures the proportion of correctly classified TB-positive and TB-negative samples out of all test samples. A high accuracy score indicates that the model is able to accurately classify TB-positive and TB-negative samples.

Precision measures the proportion of true TB-positive cases out of all positive predictions, while recall measures the proportion of true TB-positive cases out of all actual TB-positive cases. A high precision score indicates that the model is able to accurately predict TB-positive cases, while a high recall score indicates that the model is able to correctly identify all TB-positive cases.

The F1-score is the harmonic mean of precision and recall, and provides a single score that takes both metrics into account. A high F1-score indicates that the model is both accurate and reliable in predicting TB-positive cases.

Overall, the cloud-based web application for rapid and precise detection of tuberculosis using SVM can provide a valuable tool for healthcare providers to quickly and accurately identify TB-positive cases and initiate appropriate treatment. The application can help to reduce the burden of TB on global health and improve patient outcomes by facilitating early detection and treatment.

VII. CONCLUSION

In the present work, results of automatic classification of medical images are presented in two categories: with and without tuberculosis. To carry out the classification, features are extracted using deep learning and the RESNET50 neural network. Cross-validation and the formation of training and test sets were the two classification scenarios used. The scenario with the best results was the one in which the training and test sets were formed with an accuracy greater than 85%. The classification method that shows the best performance in the two scenarios implemented in this work is SVM. As can be seen in the results obtained in the present work, these far exceed chance and allow to carry out the classification of images in an efficient way. Computer tomography (CT) of the abdomen, CT of the head, magnetic resonance imaging (MRI) of the brain, and MRI of the spine were all used in this investigation. Our suggested CNN architecture could automatically categorize these 4 sets of medical photos by image modality and anatomic location after converting them to JPEG (Joint Photography Experts Group) format. In both the validation and test sets, we achieved outstanding overall classification accuracy (>99.5 percent). The collected results allow us to assess the viability of the methods adopted. It also allows us to identify the best classification scenario and machine learning method to carry out the classification of radiographs with and without tuberculosis.

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